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Determinants of the long-term degradation rate of photovoltaic modules: A meta-analysis

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ABSTRACT

A critical factor in determining the ecological and economic benefits of photovoltaic (PV) investments is the continuous decline in power output, known as degradation rate, and the consequent projected lifespan of the installed modules. To derive the aggregated effect of all degradation rates of outdoor exposed PV modules across the existing literature and explain the large differences among reported rates, we conducted a meta-analysis using various moderator variables, including climatic conditions, cell technology, methodological characteristics, and publication characteristics. The analysis of 80 primary studies, reporting 610 degradation rate observations, revealed a median degradation rate of 0.94 %/year and indicated that cell technology, mounting location, and methodological choices in the study design significantly influence reported degradation rates. We predict an average lifespan of 47 years for well-ventilated crystalline silicon (c-Si) modules in cold climates. These findings provide guidance for the future expansion of the photovoltaic fleet, aiming to enhance long-term performance.

Abbreviations

PV	Photovoltaic
c-Si	Crystalline silicon
MAER-Net	Meta-Analysis of Economics Research Network
PICOS	Population, intervention, comparator, outcome and study design
AC	Alternating current
MC^3	Markov Chain Monte Carlo model composition
μm-Si	Micromorph silicon
HIT	Heterojunction PV modules
a-Si	Amorphous silicon
CdTe	Cadmium telluride
CIS	Copper indium selenide
CIGS	Copper indium gallium selenide
%pt.	Percentage point
I-V	Current-voltage
Notation	
H_0	Null hypothesis
H_1	Alternative hypothesis
n_1	Number of observations in the interval below the threshold
n_2	Number of observations in the interval above the threshold

1. Introduction

In 2022, the global cumulative installed capacity of PV systems reached an all-time high of 1 TWp [1], accounting for 4.5 % of total global electricity generation [2]. However, to meet the UN Sustainable Development Goal of universal access to affordable and clean energy, it is essential to increase the total energy output of PV systems. This can be achieved by expanding the capacity and improving the long-term performance of PV systems, which varies significantly around the world, for example, due to different environmental conditions. Therefore, it is crucial for new PV installations to understand the causes of degradation and accurately predict the degradation rate and subsequent lifespan of these systems, leveraging the already existing large record of scientific evidence in this field.

Numerous studies, including Skoczek et al. [3], Chandel et al. [4], and Carigiet et al. [5] have examined the long-term performance of different PV modules, resulting in a multitude of reported degradation rate observations obtained under diverse climatic conditions and applying a wide range of measurement and evaluation techniques. Several scholars have further explored the impact of this heterogeneity on reported performance losses. For example, Dubey et al. [6] measured a large number of PV installations in India and investigated the variation in degradation rates by sorting them by climate zone, module size, system size, and variations in the installation. Moreover, Markides et al. [7] measured PV arrays, applying different analysis methods, and found

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Table 1
Typology of the moderator variables investigated to cause differences in reported degradation rates.

Moderator category	Moderator subcategory	Description
Geopraphical characteristics	Simplified Koeppen-Geiger classification	General climatic conditions under which the PV modules are installed
Installation characteristics	Technology, Installation date, Mounting location, Mounting type, Number modules	Differences in the type or setup of PV installation
Methodological characteristics	Measurement type, Observation length, Known defect	Differences in the methodological approach of the study
Publication characteristics	Citations, Author type, Publication type	Key indicators of a publication's impact and its authors

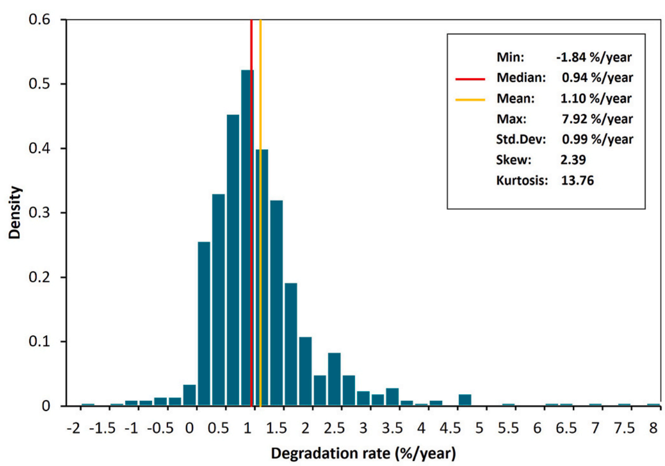

Fig. 1. Histogram of all 698 degradation rates (%/year) included in our sample. The median degradation rate is displayed by the red line and the mean degradation rate is displayed by the orange line. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

them to affect the resulting performance loss rate. In light of the variety of past research results and the lack of a comprehensive synthesis, the seminal literature review by Jordan and Kurtz [8] with an extension by Jordan et al. [9] presented the first systematic aggregation of long-term degradation rates of PV modules and systems. Using descriptive statistics to summarize the reported degradation rates of almost 200 studies, they derived a median annual degradation rate of 0.9 %/year with the PV cell technology and the primary author's methodological choices as the main determinants of the observed heterogeneity among the reported rates. Moreover, the authors found evidence indicating that elevated temperatures due to hotter climates and mounting configurations may lead to an increase in degradation rate in some PV products.

Although the analytical review by Jordan et al. contributes significantly to the accumulation of knowledge about PV degradation, a systematic and statistical meta-analysis can further improve the understanding of the underlying causes of differences among reported degradation rates. A meta-analysis is a statistical method that integrates empirical results from multiple primary studies on the same research question to determine whether and to what extent an effect is empirically supported [10]. Consequently, we conducted a meta-analysis using a machine learning-assisted literature search and Bayesian model averaging to address model uncertainty in the meta-regression model, which includes a large set of determinants of PV degradation. We follow the quality guidelines by Havranek et al. [11] (Supplementary Table 1) and best practices of recent meta-studies including Ghosh and Prasad [12] and Chaikumbung et al. [13]. This approach also allows us to account for the sampling bias identified as a serious concern by Jordan et al. [9] and to use the meta-regression estimates to predict the lifespan of PV modules considering all previously reported degradation rates. In comparison, a similarly powered primary study would require a data set of comparable size and diversity to our meta-data set, which entails about 70.000 individual modules installed at various locations all over the world since 1979.

By consolidating the literature on the long-term degradation of PV modules published until 2023, we discovered a mean and median degradation rate of 1.1 %/year and 0.94 %/year, which is slightly higher than previous findings by Jordan et al. The heterogeneity analysis via meta-regression implies that the cell technology, climatic conditions, mounting location, and the methodological approach, specifically the measurement type, are the main drivers of differences in reported degradation rates. Based on these findings, we predict an average lifespan of 47 years for a rooftop installation of the market-leading c-Si modules.

The following sections of the paper are structured as follows: Section 2 outlines the methodology applied in this meta-analysis. Section 3 presents and discusses the empirical findings, including the results of the meta-regression, while Section 4 provides the conclusions.

2. Methodology

2.1. Data and sample construction

To derive the factors causing the heterogeneity in reported degradation rates, we constructed our metadata set by conducting a string-based keyword search of the scientific literature on photovoltaic degradation following the Meta-Analysis of Economics Research Network (MAER-Net) reporting guidelines [11]. As databases, we used Google Scholar, Scopus, and IEEE Xplore. The search strings were developed in an iterative process, following the PICOS (population, intervention, comparator, outcome, and study design) model recommended by the Campbell Collaboration (Supplementary Table 2). We applied this approach by reviewing the results of each search iteration, narrowing the search if the results were deemed largely irrelevant, and broadening the search approach if known relevant studies were missing. This resulted in a dataset of 2,503 studies of which 318 were duplicates. To improve the identification of relevant studies and increase the efficiency of the abstract screening process, we used the active learning software ASReview [14]. The open-source tool, once provided with an initial assessment of appropriate literature to include, suggests the most relevant papers first, displaying only key information, namely title, abstract, and a link to the full text. The system continuously learns from user input and improves its recommendations with each selection.

The following selection criteria (Supplementary Table 3) were applied during full-text screening to identify our final sample of studies (Supplementary Table 4): (1) Studies must report or allow for the calculation of the annual degradation rates of a PV module or array. (2) We excluded studies that employed alternating current (AC) output data to calculate degradation rates, as we solely focused on module degradation. Otherwise, factors such as inverter degradation could have affected our findings. (3) The PV modules must be exposed to outdoor conditions for at least five years. This condition ensures accurate degradation rate measurements, as short observation lengths are more susceptible to seasonal variations and initial module stabilization [15]. (4) Although these selection criteria aim to isolate studies specifically addressing the irreversible material degradation of PV modules,

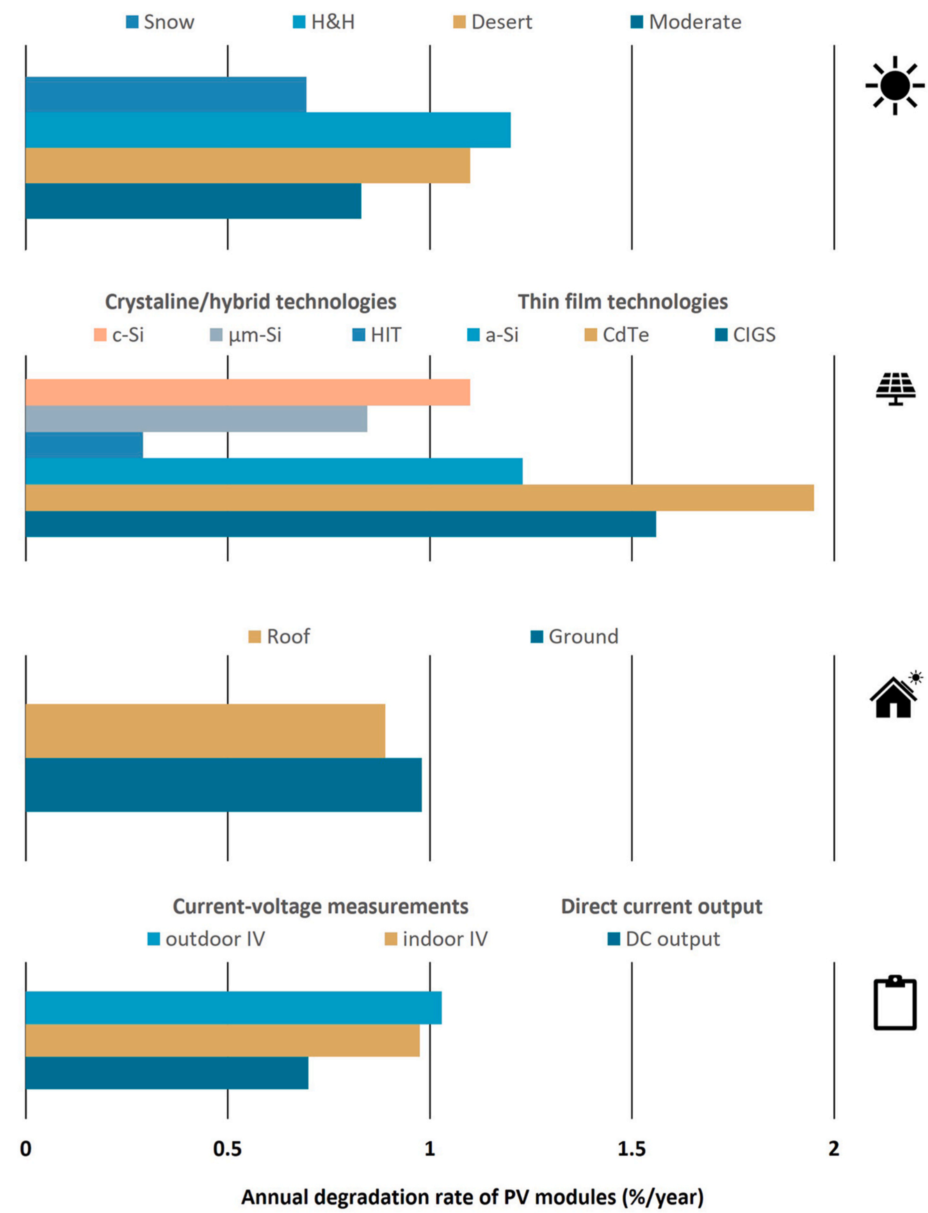

Fig. 2. Median degradation rate for selected subcategories. The figure depicts the median degradation rates (%/year) per moderator within the subcategories climate, technology, mounting location, and measurement type.

achieving this is challenging because the term "degradation rate" is frequently used interchangeably with "performance loss rate" in the existing literature. Unlike degradation rate, performance loss rate encompasses both reversible and irreversible performance losses at the system level [16]. Consequently, the degradation rates reported in the sample often reflect additional causes of performance loss, such as soiling, shading, or wiring losses. Attempting to assign the label "performance loss rate" based on primary studies is challenging, as some studies provide only limited information. For example, details about module cleaning schedules or shading issues are frequently missing. Assigning this label contrary to the original authors' specifications would therefore inevitably require subjective intervention by the authors of the meta-analysis. Nevertheless, to address this ambiguity, we therefore included moderators that account for specific aspects of performance loss that can be reliably coded across the entire meta-data sample, for instance, information regarding whether measurements were made at the module or array level. To perform the heterogeneity analysis on the complete set of moderator variables, we excluded observations from studies that did not publish the information needed to code the full set of 41 moderator variables. The complete overview of the systematic literature search process is shown in the PRISMA flowchart (Supplementary Fig. 1). The data was manually coded by a primary reviewer, who made updates as new information emerged. This process was continuously supervised by a secondary reviewer. Some studies only presented the observed degradation rates in graphical form, necessitating the extraction of the data from these studies using a digitalization tool.

Applying the selection criteria resulted in a final sample of 80 primary studies, most of which report more than one degradation rate observation, providing us with a metadata set of 610 observations that are based on ~70,000 individual modules. The modules under investigation were deployed in 27 countries across Europe (23 %), Africa (26 %), Asia (33 %), Americas (15 %) and Australia (1 %). The module installation dates range from 1979 to 2017, encompassing various cell technologies including c-Si and thin film cells. The last study was added in October 2023.

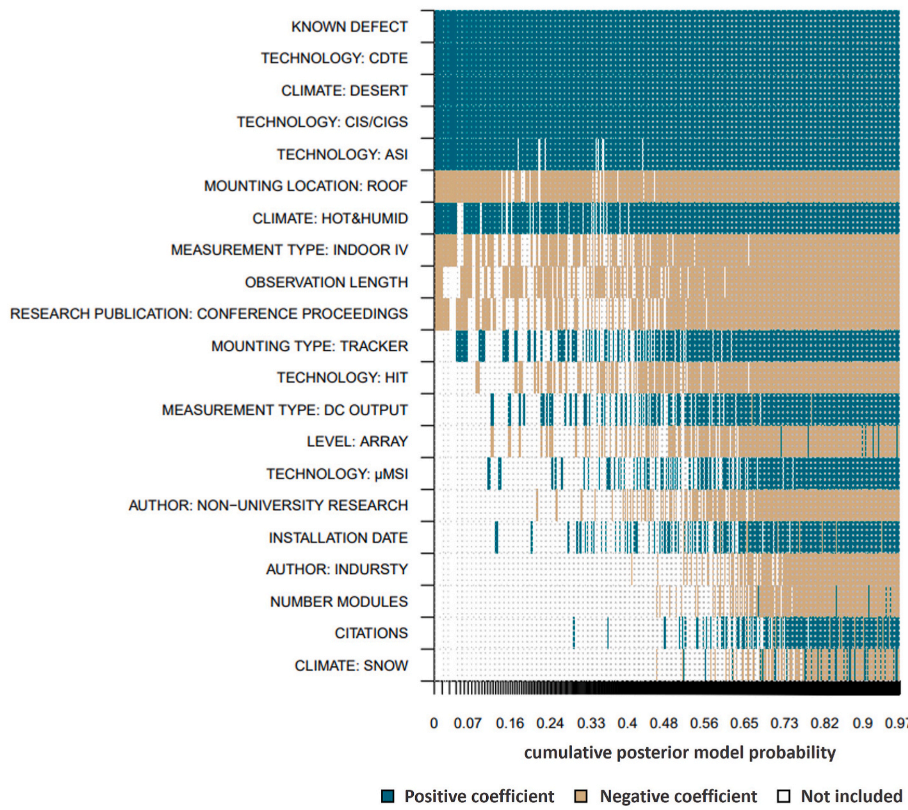

Fig. 3. Factors influencing the reported degradation rates. The figure displays the results of the Bayesian model averaging for the moderator variables. The columns represent the individual models, with degradation rate as the response variable. The moderators (explanatory variables) are sorted by their inclusion probability in descending order, indicating the likelihood of their inclusion in the model. The horizontal axis shows the cumulative posterior model probabilities, which is a measure of the models' fit. Models on the left are of higher fit. The cells highlighted in turquoise indicate the model inclusion of a variable with a positive sign, while those in brown indicate the inclusion of a variable with a negative sign. Uncolored cells indicate that a variable is not included in the respective model. The model averaging is based on the unit information g-prior and the dilution prior, which takes collinearity among the moderators into account. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

To conduct the meta-analysis, we relied on the primary researchers to transparently report the environmental conditions, experimental setup, and methodological decisions in their work. This allowed us to manually code a wide set of observable study design aspects, referred to as moderator variables. By carefully reading the 80 primary studies in our sample, along with their supplementary materials, we categorized the 41 coded moderator variables, most of which were binary variables, into four categories: geographical characteristics, installation characteristics, methodological characteristics, and publication characteristics (Table 1).

In the meta-regression, we simultaneously analyzed the influence of these moderators (the explanatory variables in the regression) on the dependent variable, which is the percentage degradation rate per year. Although we initially included all 41 moderators in our meta-data set, we ultimately had to exclude some of them due to multicollinearity, leaving us with a final list of 29 moderators (Supplementary Table 5). Specifically, high correlation was observed between moderators within the category "methodological characteristics" because primary authors often follow similar processes in determining degradation rates. Therefore, we suggest that findings related to the measurement type must be interpreted more generally and considered as a result of methodological differences that might also be influenced, for example, by the statistical analysis technique or the performance metric employed by the primary study authors, both of which were coded in the initial meta-data set.

2.2. Bayesian model averaging

Bayesian model averaging was employed to address model uncertainty in the meta-regression analysis. When applying meta-regression, we need to avoid the inclusion of irrelevant or redundant variables in the model, which could reduce the precision of the estimates of the explanatory variables [17]. The concept of Bayesian model averaging involves performing the meta-regression analysis with multiple subsets of explanatory variables, instead of choosing a single regression specification and averaging across all possible combinations. Thereby, Bayesian model averaging constructs a weighted average based on the posterior model probability, which can be interpreted as a measure of model fit comparable to the adjusted R^2 in regression analysis [18]. The posterior inclusion probability is used to evaluate the importance of the explanatory variables. It indicates the probability that a variable is included in the correct regression model and can be seen as the aggregate of all posterior model probabilities across models including this variable [19]. Following Jeffreys [20], we defined the effect between the dependent and explanatory variable to be "weak" if the inclusion probability is between 0.5 and 0.75, "substantial" if it is between 0.75 and 0.95, "strong" for values between 0.95 and 0.99, and "crucial" above 0.99. Since calculating 2^k potential regression models would require significant computing resources, the Markov Chain Monte Carlo model composition (MC^3) was used to only consider the models with the highest posterior model probability [18].

When applying Bayesian model averaging, researchers must make assumptions about both the prior distribution of parameters within the model and the model itself, which can have a significant impact on the results obtained [19]. We applied the dilution prior of George [21], which takes into account the collinearity of the variables in the model by multiplying the model probabilities with the determinant of the

Table 2
Numerical results from the heterogeneity analysis.

Moderator variable	Bayesian model averaging Variable selection	Weighted meta-regression	
	Inclusion probability	Model (1)	Model (2)
INTERCEPT	1.000	0.556***	1.001***
Geographical characteristics			
CLIMATE: DESERT[1]	1.000	0.642**	0.322
CLIMATE: HOT&HUMID[1]	0.771	0.486***	0.327
CLIMATE: SNOW[1]	0.047	−0.032	−0.323**
Installation characteristics			
TECHNOLOGY: CIS/CIGS[2]	1.000	0.900*	1.255***
TECHNOLOGY: CDTE[2]	1.000	1.127***	1.675***
TECHNOLOGY: HIT[2]	0.336	−0.332**	−0.447**
TECHNOLOGY: ASI[2]	0.858	0.599***	0.579**
TECHNOLOGY: μMSI[2]	0.168	0.558***	0.181
MOUNTING LOCATION: ROOF[3]	0.820	−0.308**	−0.396***
MOUNTING TYPE: TRACKER[4]	0.380	–	–
LEVEL: ARRAY[5]	0.179	–	–
Methodological characteristics			
NUMBER MODULES	0.071	–	–
MEASUREMENT TYPE: DC OUTPUT[6]	0.236	0.214	−0.219
MEASUREMENT TYPE: INDOOR IV[6]	0.515	−0.424*	−0.606***
INSTALLATION DATE	0.155	–	–
OBSERVATION LENGTH	0.485	–	–
KNOWN DEFECT	1.000	0.825***	0.618***
Publication characteristics			
CITATIONS	0.069	–	–
AUTHOR: INDURSTY[7]	0.073	–	–
AUTHOR: NON-UNIVERSITY RESEARCH[7]	0.165	–	–
RESEARCH PUBLICATION: CONFERENCE PROCEEDINGS[8]	0.423	–	–
No. of studies	80	80	80
No. of observations	610	610	610

Notes: The response variable in the models is the degradation rate. The left panel shows the inclusion probability of the Bayesian model averaging which involves running numerous regressions with different subsets of the 2^{29} possible moderator combinations. Moderators with high inclusion probabilities are more frequently included in these regression models. The right-hand panel reports the estimates of the weighted meta-regression coefficients, including only the moderators or subcategories of moderators (like technology) with inclusion probabilities above 0.50. For instance, the coefficient 0.642 indicates that studies measuring modules exposed in desert conditions display, on average, 0.642 percentage point higher degradation rates.
Standard errors in the weighted meta-regression are clustered at the study level.
Model (1): Weighted meta-regression with study-reliability measure computed by the authors as weights.
Model (2): Weighted meta-regression with inverse number of degradation observations per study as weights.
Base groups of the dummy variables that were selected based on their prevalence as the most common specification: [1]moderate, [2] c-Si, [3] ground, [4] fixed tilt, [5] module, [6] outdoor IV, [7] university, [8] journal article.
$^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

correlation matrix of the variables that are added to the model. A higher collinearity among variables leads to a determinant closer to zero, resulting in a decrease in the model weight. The unit information g-prior was used, assuming that the prior information is equivalent to that of a single observation [22].

2.3. Meta-regression analysis

We applied meta-regression analysis, which allowed us to simultaneously test the impact of different explanatory variables (moderators) on a dependent variable, which is the annual degradation rate observed from the set of primary studies [23]. Continuous moderator variables were logarithmically transformed, and some moderators had to be removed due to multicollinearity, especially between moderators describing the methodology used in the primary studies. To differentiate for geographical characteristics, we assigned each observation to a simplified Köppen–Geiger climate category (Moderate, Desert, Hot and Humid, Snow), also applied by Jordan et al. [9]. A detailed explanation of the moderator variables can be found in Supplementary Table 5. To address the heteroscedasticity observed in the meta-regression analysis residuals, we applied weighted meta-regression which usually uses the standard error of the effect size estimations to assign larger weight to more precise studies [24]. As there is no standard error associated with the reported degradation rates in our study, given that they are not statistical estimations but rather real observations of the measured power decline, we developed a reliability metric constructed by the authors to assign a larger weight to more reliable degradation rate estimates (Model 1). Reliability was defined by the presence of certain quality characteristics in the primary study (Supplementary Table 6). Studies with a clear methodological description received higher reliability scores, while those lacking key details or using suboptimal methods were penalized. Failure to report methodological aspects resulted in a two-point penalty, while the absence of information about the installation and its location incurred a one-point penalty. Consequently, studies could receive up to 14 penalty points. If information about the installation or location was not transparently disclosed one penalty point was assigned. Consequently, a maximum of 14 penalty points could potentially be allocated. We also used the inverse number of degradation rate estimates reported per study to avoid studies with many reported degradation rates from overly influencing the results (Model 2). To account for within-study dependencies among multiple degradation rates taken from the same study, we report the meta-regression results with robust standard errors clustered at the study level [25]. The meta-regression coefficient obtained by applying this methodology can be interpreted as the average percentage point change in degradation rate resulting from a one-unit change in the specific moderator. Furthermore, by assigning synthetic values to the full set of moderator variables, our model facilitates the prediction of degradation rates, based on the assumptions made and the data available from the prior literature.

2.4. Analysis of publication selection bias

We applied two distinct methods to test for the presence of publication selection bias.

The Egger's test [26] is a linear test, that measures the skewness of the funnel plot, which is a scatterplot that displays the effect size against a measure of precision, commonly the standard error. However, as the PV module degradation is not estimated by the primary researcher, but rather measured, we employ the number of modules as a proxy for the standard error. This is based on the assumption that with a higher number of modules, the primary study authors are less likely to consciously bias the results, e.g. through the experimental setup or the measurement method. To test this, we examined the null hypothesis that the slope of a simple linear model, in which the degradation rate observation was regressed against the natural logarithm of the number of modules observed, was equal to zero.

Another effective test for the detection of publication selection bias that can be employed even in the absence of an uncertainty measure in the primary studies is the caliper test proposed by Gerber and Malhotra [27]. The caliper test compares the number of observations within an interval below (n_1) and above (n_2) an important threshold. Typically, these thresholds are set at the 0.01, 0.05, and 0.1 levels of statistical significance. However, it is possible to set them at other points that may be deemed desirable for the primary authors to achieve a favorable outcome in the editorial and peer-review process. Here, we defined the

Table 3
Predicted degradation rates and 95 % confidence intervals.

Roof-mounted installation								
	Moderate		Desert		Hot & Humid		Snow	
	Mean	95 % CI	Mean	95 % CI	Mean	95 % CI	Mean	95 % CI
c-Si	0.46	[0.24, 0.69]	1.10	[0.62, 1.59]	0.95	[0.59, 1.31]	0.43	[0.00, 0.86]
CdTe	1.59	[0.83, 2.35]	2.23	[1.46, 3.00]	2.07	[1.38, 2.77]	1.56	[1.08, 2.04]
Ground-mounted installation								
	Moderate		**Desert**		**Hot & Humid**		**Snow**	
	Mean	95 % CI	Mean	95 % CI	Mean	95 % CI	Mean	95 % CI
c-Si	0.77	[0.54, 1.00]	1.41	[0.83, 2.00]	1.26	[0.82, 1.69]	0.74	[0.24, 1.24]
CdTe	1.90	[1.16, 2.63]	2.54	[1.72, 3.35]	2.38	[1.68, 3.09]	1.87	[1.36, 2.37]

Notes: The table shows the Implied degradation rates by the literature of a roof-mounted and ground-mounted installation, conditional on selected values of the moderator variables. For the calculation, we use the results of the weighted meta-regression (Table 2, Model 1) and compute fitted values conditional on the definition of best practice (for example, we use 0 for the known defect variable). The 95 % confidence intervals (CI) are reported in parentheses.

thresholds at degradation rates that align with common performance guarantees, as well as at the frequently cited degradation rate published by Jordan et al. [9]. Specifically, we tested at thresholds of 0.66 %/year, 0.8 %/year, 0.9 %/year, and 1 %/year. In the absence of publication bias and with a sufficiently narrow interval, it can be assumed that there is no significant difference in the frequency of observations below and above the threshold. Hence, the caliper test, formally a one-sided binomial test, examines whether the observed pattern is consistent with the null or an alternative hypothesis that states there is an excess of observations below the threshold.

$$H_0 : \frac{n_1}{n_1 + n_2} \leq 0.5 \; vs. \; H_1 : \frac{n_1}{n_1 + n_2} > 0.5 \tag{1}$$

3. Results and discussion

3.1. Distribution of the collected degradation rate observations

Fig. 1 depicts the distribution of all collected observations and highlights their mean (orange line) and median (red line) values. The histogram is substantially right-skewed, which we explained by the fact that most modules without irregular defects degrade at similar rates. However, modules that are subjected to unusual stress that results in significant defects or near-total failures have significantly higher annual degradation rates. The histogram also shows that some studies (18 observations) reported negative degradation rates, meaning the modules performed better after the observation period than before. The reasons for this rather counterintuitive finding could lie in the methodology of performance assessment, for example, the use of manufacturer specifications, which tend to deviate from the actual performance at installation, or in large measurement errors.

3.2. Explaining the heterogeneity of PV degradation rates

For an initial analysis of heterogeneity, we calculated the median annual degradation rates for several moderator subcategories (Fig. 2): technology, mounting location, measurement type, and climate classification.

From this subcategory analysis, we found that the highly efficient heterojunction PV modules (HIT) exhibited the lowest median degradation rate of 0.29 %/year, whereas the thin-film technologies copper indium selenide (CIS), copper indium gallium selenide (CIGS) and cadmium telluride (CdTe), that are generally lighter and more flexible, degraded at a rather high median rate of 1.5–2 %/year. This is consistent with prior research, whereby the most common silicon-based cells exhibit a significantly slower rate of degradation when compared to non-silicon technologies [8,9].

Another notable observation was the distinct difference between climatic zones, with warmer climates inducing elevated degradation rates that exceeded a median of 1 %/year in our sample. Contrary to our expectations, the descriptive meta-statistics did not indicate that a more recent installation date, and therefore further technological advances, were associated with a lower level of deterioration (Supplementary Fig. 2).

As a more advanced approach compared to the univariate analysis of medians, we employed meta-regression analysis, which models the impact of all moderator variables simultaneously. The base group, which is the reference characteristic for the categorial dummy moderators, was always chosen to be the most commonly occurring value in our dataset (Supplementary Table 5). For example, since 76 % of observations are of c-Si modules, this technology was selected as the base group for the moderators measuring differences in the PV technology. For robustness, we used two different models with distinct weighting schemes: Model 1 is our baseline model and assigns a larger weight to observations from more reliable studies (Supplementary Table 6), and Model 2 assigns a smaller weight to observations from studies reporting a higher number of degradation rates observations. A problem of standard meta-regression analysis is that it ignores model uncertainty, as not all of the 29 moderator variables in the model might be equally important to explain the differences in degradation rates. Therefore, we first applied Bayesian model averaging to identify key variables driving heterogeneity (Fig. 3), which involves running many regressions with different subsets of the possible combinations of explanatory variables. The posterior inclusion probability, from now on just referred to as inclusion probability, denotes the probability that a variable is included in the true regression model. We evaluated moderators and subcategories of moderators (like technology) as key variables and added them to the reduced meta-regression model if their inclusion probability exceeded 0.5 [28] (Table 2). Moderators that failed to reach this threshold, where the relationship between the explanatory variable and the degradation rate could at best be considered weak, were found to have no explanatory power for the heterogeneity across reported degradation rates.

After selecting the key moderator variables via the Bayesian model selection (Supplementary Table 7), we estimated the weighted meta-regressions for the reduced set of variables of these key moderators (Table 2, Supplementary Table 8). The estimated meta-regression coefficients in this model can be interpreted as the percentage point (%pt.) sensitivity of the degradation rates to changes in the moderator variables.

For the climate variables, we found higher degradation rates in hotter and more humid climate zones. This was indicated by the high inclusion probability of the hot & humid (0.771) and desert (1.000) climate zones and the significant positive coefficients (0.486 %pt. and 0.642 %pt.) in the reliability-weighted Model 1. This means that, compared to the omitted base group, which is the moderate climate zone, the annual degradation was, on average, 0.642 %pt. Higher for modules located in desert climates. These results are consistent with expectations, as elevated temperature and humidity are known causes of defects in PV modules [29].

Moreover, differences in the PV installation affect the degradation rate. Thin-film technologies such as CIS/CIGS (0.900 %pt.), CdTe (1.127 %pt.), and a-Si (0.599 %pt.) were associated with significantly higher annual degradation compared to the base group of crystalline silicon, a result in line with prior literature [8,9]. In contrast, heterojunction modules exhibited a significantly lower degradation rate (−0.332 %pt.). In addition to the cell technology, the mounting location had a mitigating impact on degradation rates. We attribute this robust effect to the predominantly flat roof rack-mounted installations in our sample, which benefit from enhanced cooling due to stronger winds at elevated positions. Aside from the mounting location, modules mounted on tracking devices did not show differences in degradation rates. We included a dummy moderator for studies reporting any known defects in the PV modules, which also includes soiling. The logical assumption that modules with any visible or measurable defects, accounting for both irreversible degradation and reported reversible performance losses, are associated with increased degradation rates was confirmed by a highly significant meta-regression coefficient (0.825 %pt.). The measurement of an array of modules, as opposed to individual modules, is found to have a posterior inclusion probability of 0.179, which is below 0.5. Consequently, reversible performance losses introduced by measuring an array rather than a single module, such as wiring losses, are not significant in explaining the overall heterogeneity of reported degradation rates.

We found that different methodological choices contribute to the heterogeneity in reported degradation rates. Specifically, the use of indoor current-voltage (I-V) measurement, employed in seven percent of the observations, was on average, associated with significantly lower degradation rates (−0.424 %pt.) compared to outdoor I-V performance measurements, which is the base group for this variable. As previously indicated, the installation date did not show any influence on the reported degradation rates. The same conclusion could be drawn for the observation date and the number of modules examined.

To examine whether specific publication characteristics affect the reported rates of degradation, we incorporated moderators controlling for the authors' affiliation, the publication outlet, and the number of citations. None of these variables exceeded the inclusion probability threshold for the reduced meta-regression model, suggesting they are not systematic drivers of differences in reported degradation rates.

The robustness analysis using Model 2 confirmed the findings from the baseline model. Moreover, it is important for any meta-analysis to test for the presence of publication selection bias, which refers to the phenomenon where desired or "positive" results are more likely to be published in the primary studies [30]. The Egger et al. [26] test (Supplementary Fig. 3 and Supplementary Table 9) and the Caliper test [27] (Supplementary Table 10) did not indicate a systematic bias towards publishing preferred findings. However, the caliper test reveals a higher prevalence of observations just above the 0.66 %/year threshold, suggesting a tendency to publish degradation rates associated with lifespans slightly under 30 years.

3.3. *Predicted lifespan of PV modules*

The analysis of heterogeneity unveiled that reported degradation rates are systematically influenced by various environmental, technological, and methodological factors. In addition to the heterogeneity analysis, we used the estimated meta-regression coefficients from the reliability-weighted meta-regression (Table 2, Model 1) to construct a hypothetical study that incorporates all information and reported degradation observations in the literature, while giving greater weight to aspects of the study design and data that are arguably preferable. As this "best practice" exercise is inherently subjective, we aimed to be conservative and substituted the dummy explanatory variables for their base group, which indicates the most common observation for this variable in the literature (e.g., no known defect). One exception was the measurement type. Here, we selected direct current output measurements for the hypothetical study, because outdoor I-V, which was most common, is very susceptible to greater uncertainties, for example, due to the weather at the time of measurement. We calculated the predicted degradation rate separately for roof-mounted and ground-mounted installations, for c-Si modules and the thin-film technology CdTe, as well as for all four climatic zones (Table 3).

The predictions indicated that based on all existing information from the literature and assuming the best practice study design mentioned above, the widely employed c-Si modules degrade on average at a rate between 0.43 %/year and 1.41 %/year, depending on the climatic zone and the installation type. In contrast, thin-film modules exhibit average degradation rates twice as high ranging from 1.56 %/year to 2.54 %/year. Consequently, the meta-results imply rooftop-mounted installations in cold or moderate climates as the most favorable scenario, because these conditions result in the lowest degradation rates. Using these degradation rates, we can estimate the lifespan of PV modules by applying the commonly used definition of failure, which is denoted by a 20 % decline in performance. With this approach, a predicted average degradation rate of 0.43 %/year equates to 47 years of lifespan.

4. Conclusion

We conducted a systematic and quantitative review of the long-term degradation rate of field-aged photovoltaic modules by collecting 610 degradation rates from 80 primary studies and found a mean and median annual degradation rate of 1.1 %/year and 0.94 %/year indicating a distribution skewed towards high degradation rates.

We performed Bayesian model averaging and weighted meta-regression analysis to identify factors responsible for the large heterogeneity in reported degradation rates. The results identified the climatic conditions, mounting location, and photovoltaic cell technology to be the main drivers of differences. Specifically, cold and dry environments were identified as optimal locations to maximize the photovoltaic lifespan. Well-ventilated mounting configurations have been shown to decrease degradation and should be a primary consideration when designing and implementing new power stations, besides an appropriate selection of cell technology. Notably, the methodological techniques of the researchers cause significant variation in reported degradation rates. This highlights the importance of rigorous transparency and an urgency for consistent approaches when observing degradation rates.

Based on the estimated meta-regression results, we predicted the degradation rate of new photovoltaic modules and found c-Si modules installed in cold climates and mounted in a way that allows for good ventilation to degrade on average at 0.43 %/year which translates to 47 years of lifespan. Furthermore, the predictions show that crystalline silicon-based modules deteriorate at substantially lower rates compared to the high degradation rates found in thin-film CdTe and CIS/CIGS modules, for which the meta-results suggest an average lifetime of only 8–13 years, which contrasts sharply with the 25–30 years performance guarantee offered by some manufacturers.

Our research is subject to several limitations. Foremost, a lack of transparency in primary studies, as indicated by 70 studies not fully reporting their experimental setups, necessitating their exclusion from our final sample. This limitation also meant that we could not directly control for certain factors. In particular, the moderator "known defect" only accounts for reported performance limitations rather than specifically addressing individual degradation modes. Ideally, we would analyze the impact of specific causes of performance loss on degradation rates. However, such detailed information is available in only a limited number of studies, partly because not all primary authors have access to the same testing equipment. Additionally, the lack of transparency required the use of broader classifications, especially regarding moderators such as cell types and climatic conditions. Furthermore, our meta-analysis does not account for the latest technological developments, as we included only those studies that observed PV module performance for at least five years. We anticipate that the continued growth of primary research into performance losses of photovoltaic modules will enable future studies to expand on our work by analyzing literature subsamples in which all necessary information has been comprehensively reported, while still maintaining a sufficient sample size.

Despite these limitations, this meta-study accumulates the scientific knowledge on PV degradation and can serve as a reference point for future decision-making regarding PV investments, particularly concerning technology selection and installation location. The findings from this meta-analysis underscore the importance of intensive PV degradation research to expand module lifespan.

CRediT authorship contribution statement

Michael Straub-Mück: Conceptualization, Data curation, Investigation, Methodology, Formal analysis, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Jerome Geyer-Klingeberg:** Conceptualization, Investigation, Methodology, Formal analysis, Software, Supervision, Writing – original draft, Writing – review & editing. **Andreas W. Rathgeber:** Conceptualization, Formal analysis, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2025.115697.

Data availability

The code developed and the data supporting the findings is accessible via the following link GitHub link: https://github.com/michaelstraubmueck/Photovoltaic-Degradation-Rate

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